

A Neural Network Approach to Infer Optical Depth of Thick Ice Clouds at Night



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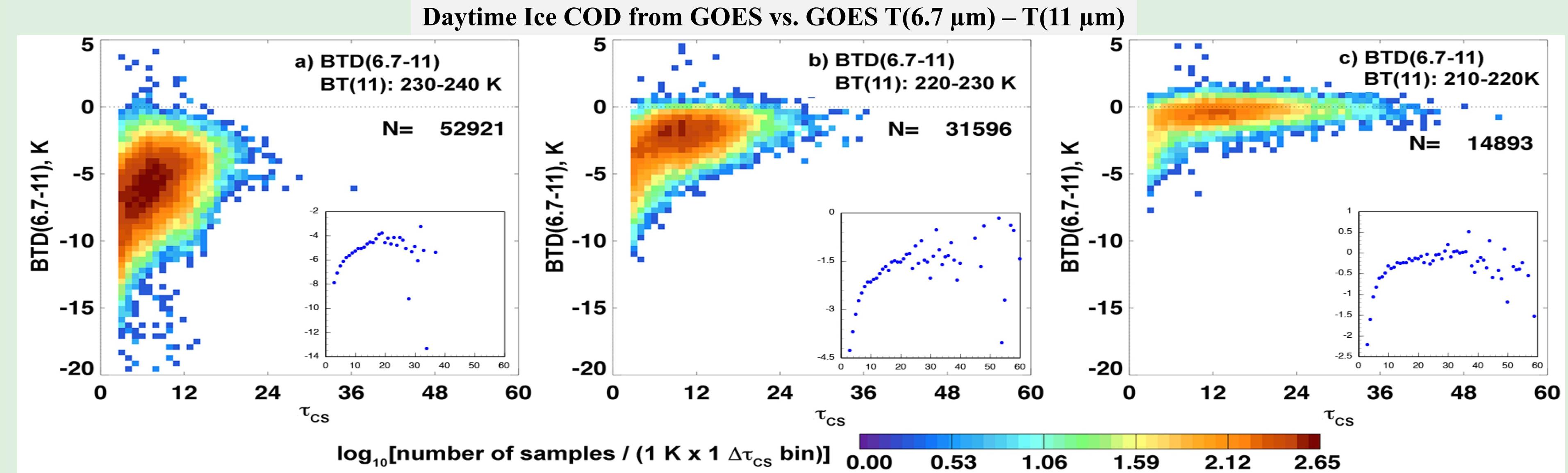
<http://clouds.larc.nasa.gov/>

Introduction

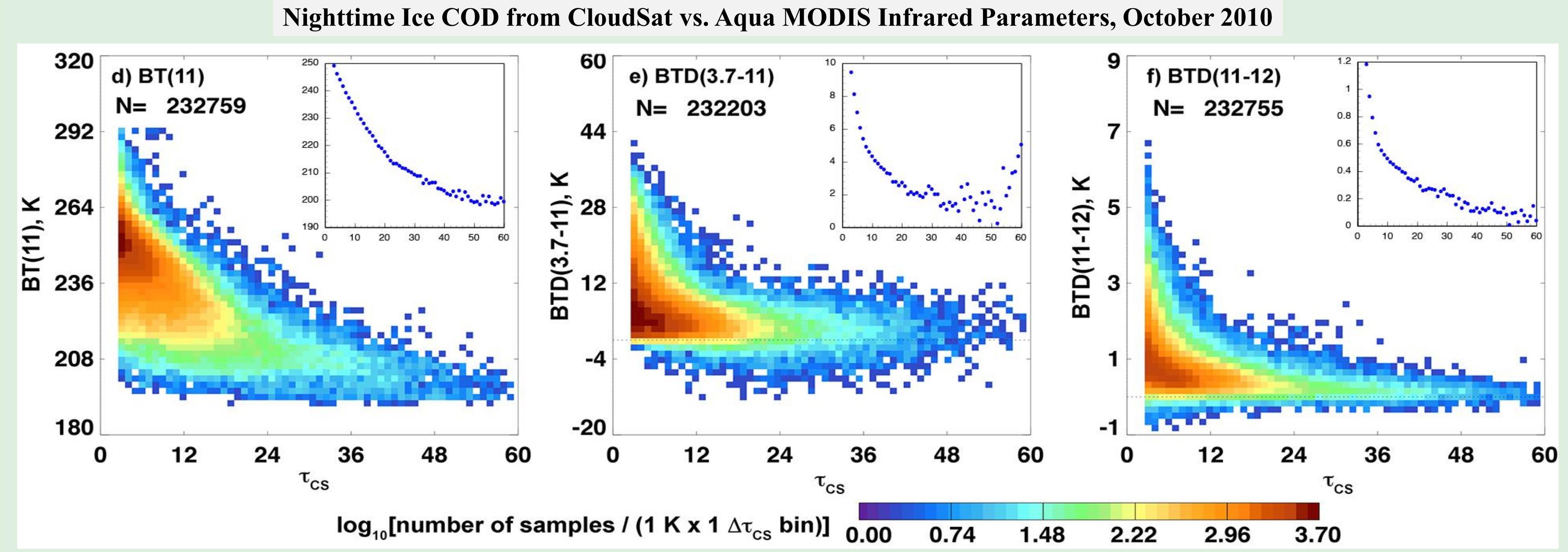
During daytime, cloud properties such as cloud optical depth (COD or τ), effective particle size R_e , and water path (WP) can be derived for a wide range of cloud thicknesses because the reflectance at visible wavelengths is sensitive to changes in optical depth from $\tau < 1$ to $\tau > 100$. At night, information from solar channels is unavailable, so retrievals of the cloud properties are typically limited to clouds having COD < 6, because the cloud is essentially a blackbody at greater optical depths, at least for the window channel wavelengths (10–12 μm) typically used for retrievals from satellite imagers. This limitation constrains the monitoring of cloud properties over the full diurnal cycle and leaves a gap in the ability to characterize clouds both at meteorological and climate scales. This paper examines the potential of using a neural network method with channels available on many current imagers to extend the range of ice cloud optical depths that can be determined from radiances measured at night. Wavelengths, 3.9, 6.7, 10.8, and 12- μm , are considered here.

Correlation of IR data and COD

Matched BTD and COD data from several months of GOES-12 data were amassed and plotted as a function of COD. The apparent correlation tends to increase as T_{cold} increases, with possible usable information up $OD = 20$ or so. Yet, even for low T_{cold} values, there may be some independent information. Note that GOES data were not screened for ML clouds that cause some of the spread or decorrelation. These observations indicate potential for using the IR data.



Several thermal channels have sensitivity to ice COD up values > 50 because of the vertical non-uniformity of the thicker ice cloud tops. This sensitivity can be seen in several other channel sets below where ice COD is estimated from the CloudSat 2B-CWC-RO product and compared with matched Aqua MODIS data from the C3M dataset (Kato et al. 2010).

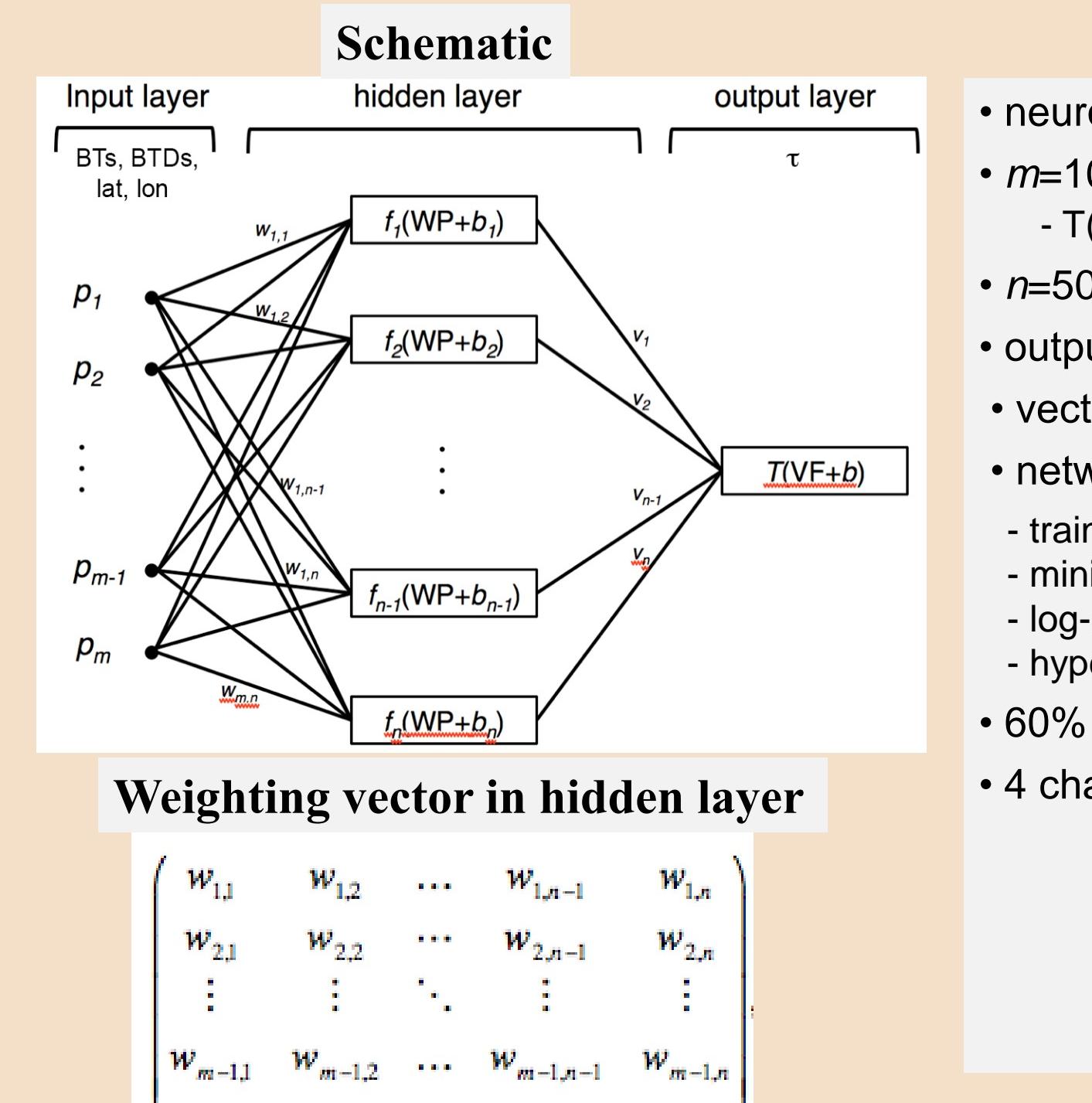


Because the values of each parameter asymptote to some value as τ increases past 16 and are a bit noisy for a given COD, a neural network was selected as the approach to obtain better estimates of ice COD from these various parameters.

DATA

- Training Set:** Matched March and October 2007 CloudSat Ver. 4 2B-CWC-RO and Aqua MODIS Infrared Brightness Temperatures
 - BCH:** Select only opaque ice clouds based on Baum et al. (2000), Choi et al. (2007), & Hong et al. (2010), only use $T_{11} < 260 \text{ K}$ (**BCH** method)
 - Ideal:** Use only pixels selected by BCH that have $\tau_{\text{CS}} \geq 8$. No thin clouds included.
 - Use up to 10 input parameters, e.g., T_{11} , $\text{BTD}(11-12)$, $\text{BTD}(3.7-11)$, $\text{BTD}(6.7-11)$, $\text{BTD}(11-12)$, LAT, LON
 - Compute ice COD by integrating CloudSat CWC and R_e profiles for $T < 0^\circ \text{ C}$ (for $T > 0^\circ \text{ C}$, use linearly weighted fraction of COD between -20° C and 0° C)
- Validation Set:** Matched March and October 2008 CloudSat COD and Aqua MODIS Infrared Brightness Temperatures
 - Test with both **BCH** and with Shortwave-infrared Split-window Technique (**SIST**, Minnis et al. 2011) selections of opaque ice cloud pixels
- Sample Images:** to illustrate results

APPROACH: Ice Cloud Optical Depth using a Neural Network (ICODIN)

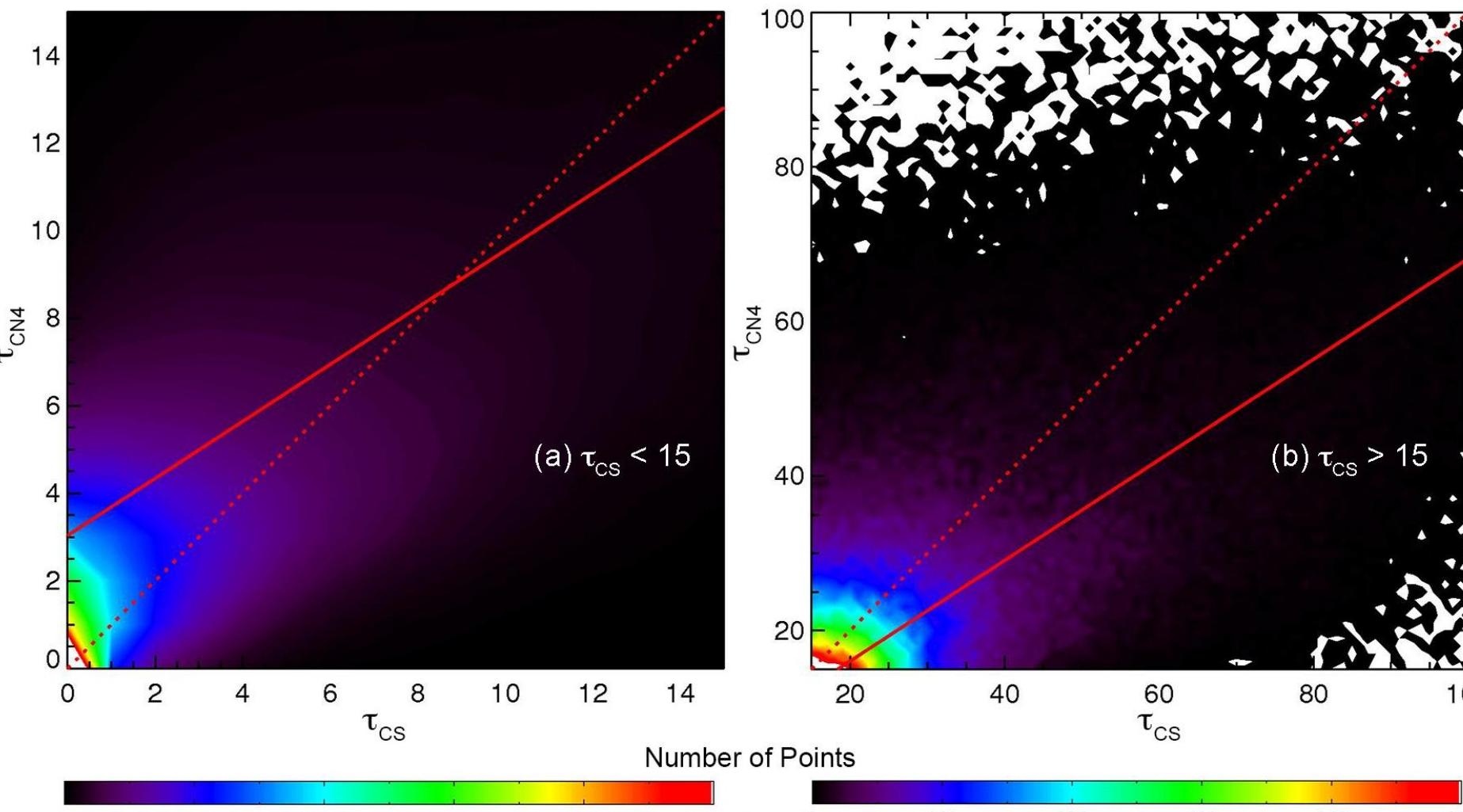


- neurons of input layer: vector $\mathbf{P}(p_1, p_2, \dots, p_{m-1}, p_m)$, where m is number of input neurons or parameters.
- $m=10$ neurons of \mathbf{P}
 - $T(3.7)$, $T(6.7)$, $T(11)$, and $T(12)$, $\text{BTD}(3.7-6.7)$, $\text{BTD}(3.7-11)$, $\text{BTD}(6.7-11)$, $\text{BTD}(11-12)$, LAT, LON
- $n=50$ neurons are used in the hidden layer for training, 1 neuron (COD) in output layer
- output layer weighting vector, $\mathbf{V}(v_1, v_2, \dots, v_{n-1}, v_n)$: weights between hidden and output neurons
- vector, $\mathbf{B}(b_1, b_2, \dots, b_{n-1}, b_n)$: bias in the hidden layer and b is bias in the output layer
- network training function of Bayesian regulation backpropagation is used for three-layer neural network
 - training function updates the weight and bias values according to Levenberg-Marquardt optimization
 - minimizes squared errors & weights, then finds the correct combination to produce a network that generalizes well
 - log-sigmoid transfer function $s(x)$ to propagate to the hidden layer
 - hyperbolic tangent sigmoid transfer function $t(x)$ to propagate to the output layer
- 60% of 2007 data used for training, 20% for updating, and 20% for testing
- 4 channel combinations were used
 - ICODIN4:** all ten parameters
 - ICODIN3a:** no 3.7 μm
 - ICODIN3b:** no 6.7 μm
 - ICODIN3c:** no 12 μm

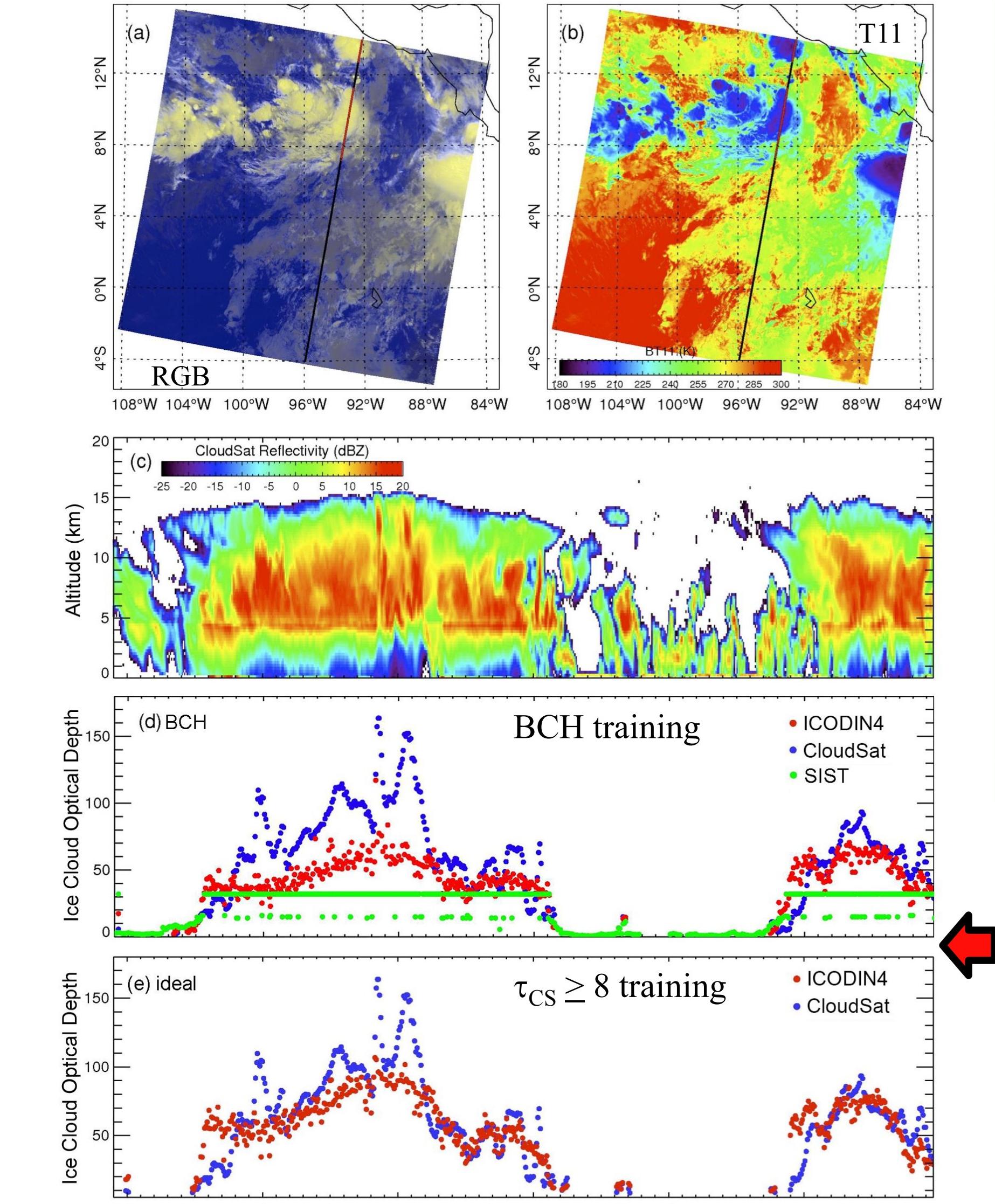
RESULTS: Opaque from BCH

- Opaque defined by MODIS data (BCH method)

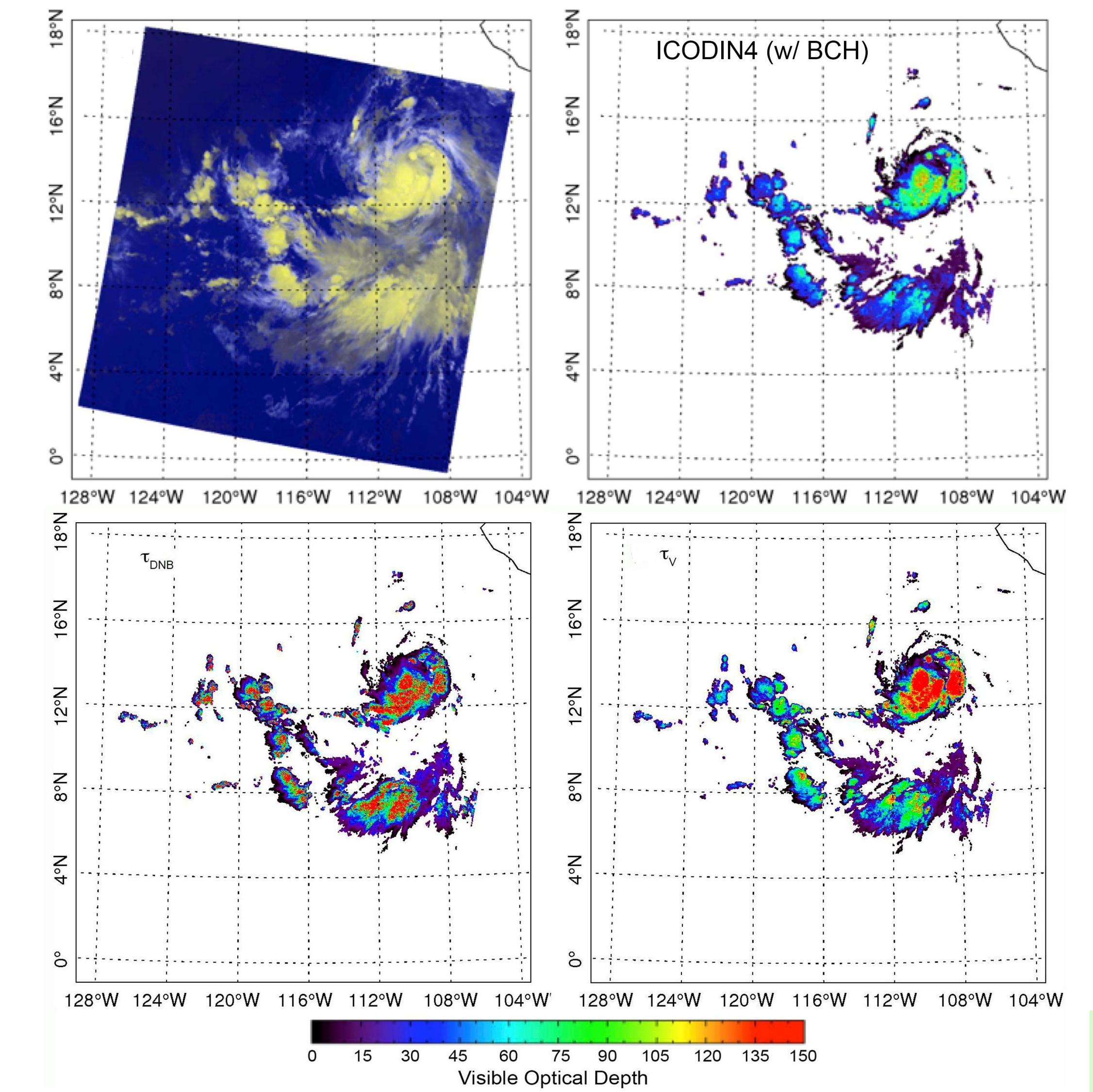
BCH Training Results



Aqua MODIS/CloudSat data and retrievals (108°W-84°W, 4°S-15°N), 0800 UTC, 6 June 2008

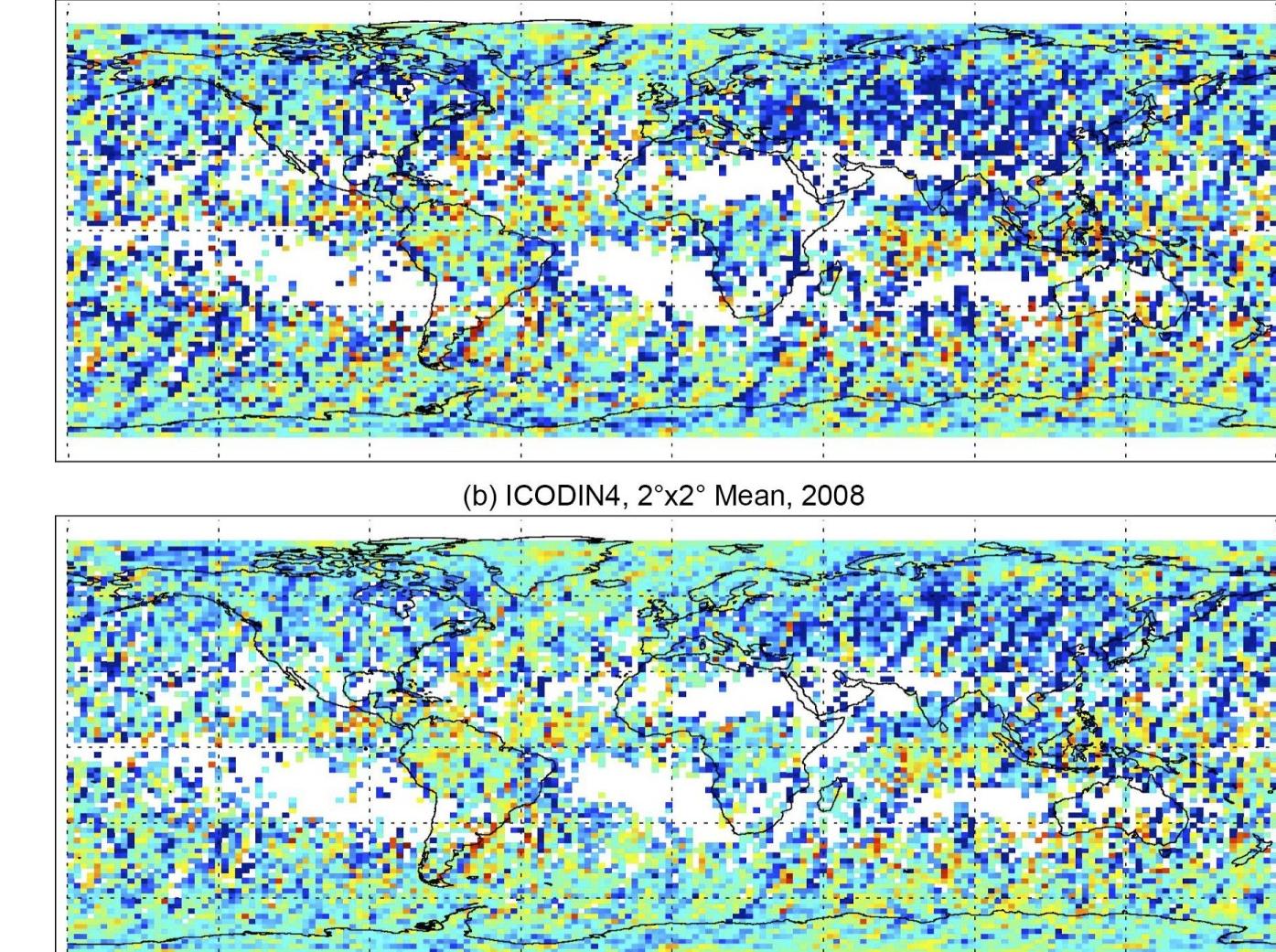


SNPP VIIRS DNB & ICODIN retrievals, 0925 UTC, 5 July 2012

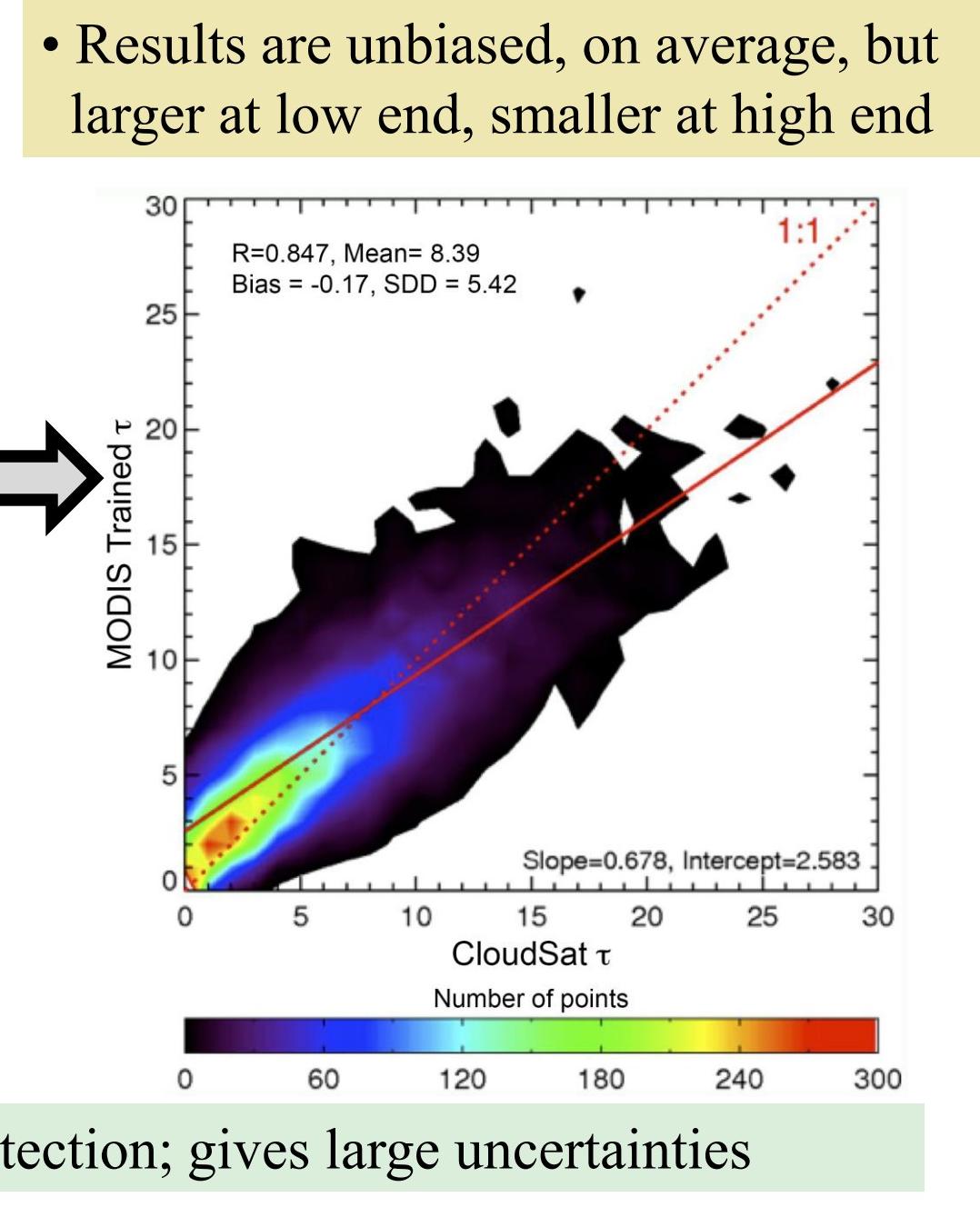


Regional COD comparisons with validation dataset

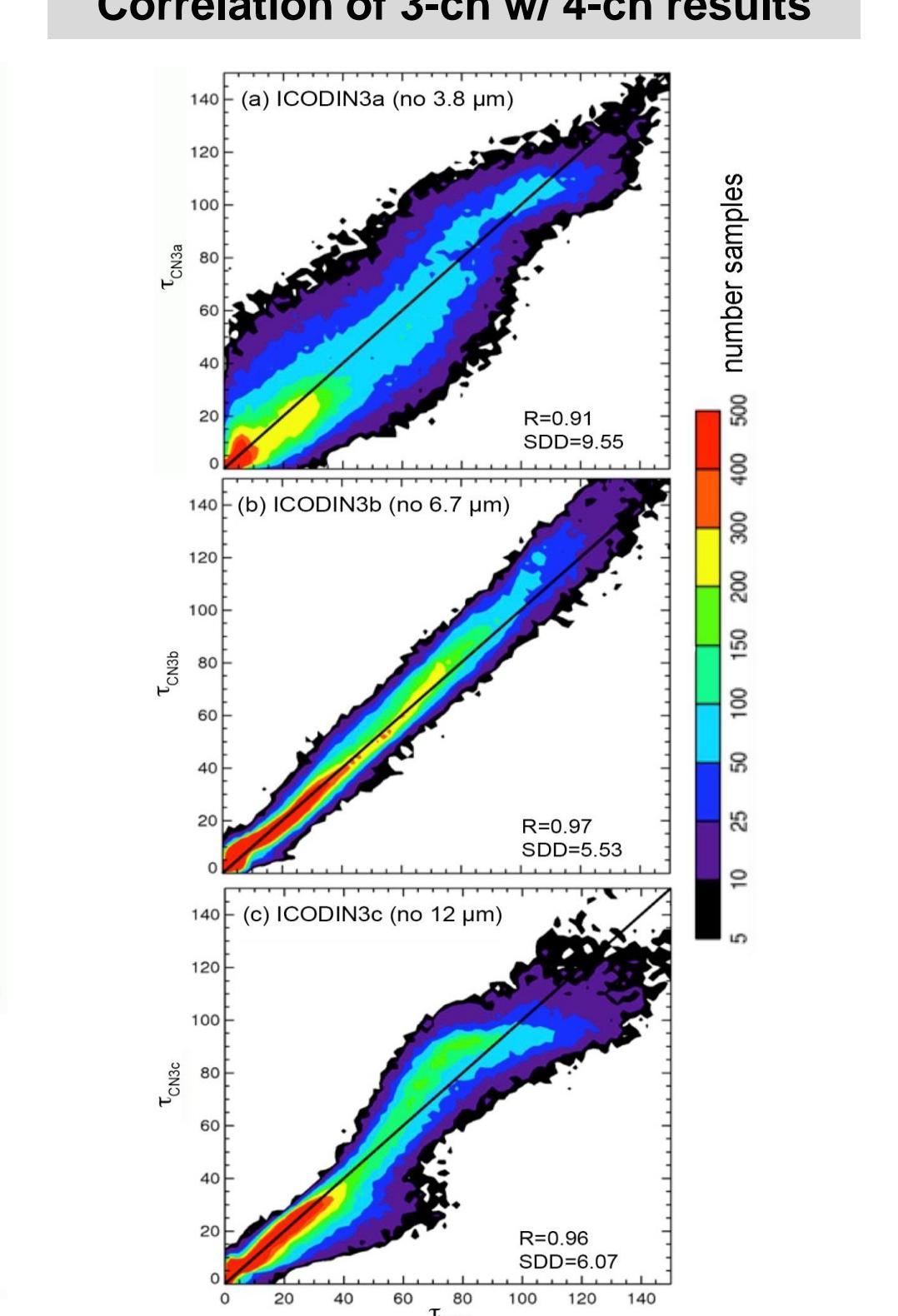
(a) CloudSat, 2'x2' Mean, 2008



• Results are unbiased, on average, but larger at low end, smaller at high end



• BCH training reveals shortcomings in opaque cloud detection; gives large uncertainties



COD Difference Statistics ICODIN-CloudSat, BCH Training

| Retrieval Method | Year | Mean | R | Bias | Bias (%) | SDD | SDD (%) |
|--------------------------------|------|------|------|-------|----------|------|---------|
| BCH opaque only | | | | | | | |
| ICODIN4 | 2007 | 8.85 | 0.80 | -0.07 | -0.8 | 8.73 | 99 |
| 3.7, 6.7, 11, 12 μm | 2008 | 8.50 | 0.78 | -0.10 | -1.2 | 8.89 | 105 |
| ICODIN3a | 2007 | 8.95 | 0.79 | -0.05 | -0.6 | 9.20 | 103 |
| ICODIN3b | 2007 | 8.83 | 0.79 | -0.09 | -1.0 | 8.91 | 101 |
| 3.7, 11, 12 μm | 2008 | 8.60 | 0.75 | -0.07 | -0.8 | 9.45 | 110 |
| ICODIN3c | 2007 | 8.86 | 0.80 | -0.05 | -0.6 | 8.80 | 99 |
| 3.7, 6.7, 11 μm | 2008 | 8.51 | 0.77 | -0.10 | -1.2 | 9.13 | 107 |
| SIST | 2007 | 7.40 | 0.63 | -2.42 | -24.6 | 12.2 | 124.4 |
| Ideal | 2008 | 7.16 | 0.64 | -2.19 | -23.4 | 11.6 | 124.4 |
| Ideal (BCH & CloudSat opaque) | | | | | | | |
| Ideal ICODIN4 | 2007 | 21.8 | 0.73 | -0.07 | -0.3 | 13.2 | 61 |
| 3.7, 6.7, 11, 12 μm | 2008 | 21.3 | 0.71 | -0.33 | -1.5 | 13.5 | 63 |

Summary

- Neural network using multispectral IR data can improve ice COD estimates at night
 - unbiased results, on average, and 21% reduction in random error
 - SDD ~ 100% when BCH or SIST selects opaque clouds
 - using $\tau_{\text{CS}} > 8$ to train yields bias of 0% and SDD of 63% for true opaque cloud
 - using BCH gives 20% bias and 80% SDD
 - can be used for any modern imager dataset
- Need improved method for diagnosing optically thick ice clouds from multispectral IR
- Improvements can be made
 - use T, RH profiles, Zscf, cloud heterogeneity
 - use to discriminate contiguous vs. high ice over low water clouds
 - test and adjust for non-nadir views

References

- Baum, B. A., and Coauthors (2000), Remote sensing of cloud properties during SUCCESS: II. Cloud thermodynamic phase, *J. Geophys. Res.*, **105**, 11,781–11,792, doi:10.1029/1999JD901090.
- Choi, Y. S., C.-H. Ho, M.-H. Ahn, and Y. M. Kim (2007), An exploratory study of cloud remote sensing capabilities of the Communication, Ocean and Meteorological Testbed (COMS) imagery: *Int. J. Remote Sens.*, **28**, 4715–4732, doi:10.1080/0143160701264235.
- Hong, G., et al. (2010a), Detecting opaque and nonopaque tropical upper tropospheric ice clouds: A trispectral technique based on the MODIS 8-12 μm window, *J. Geophys. Res.*, **115**, D001404, doi:10.1029/2010JD014044.
- Kato, S., et al. (2010), Performance of CloudSat Cloud Profiling Algorithm in Clouds with High Vertical Profile Overlap, *J. Geophys. Res.*, **115**, D001227, doi:10.1029/2009JD012277.
- Minnis, P., et al. (2011b), CERES Edition-2 cloud property retrievals using TRMM VIRS and Terra and Aqua MODIS data, Part I: Algorithms, *IEEE Trans. Geosci. Remote Sens.*, **49**, 4374–4400.
- Minnis, P., G. Hong, S. Sun-Mack, W. L. Smith, Jr., Y. Chen, and S. Miller, 2016, Estimation of nocturnal opaque ice cloud optical depth from MODIS multispectral infrared radiances using a neural network method, *J. Geophys. Res. Atmos.*, **121**, doi:10.1002/2015JD024456.
- Smith, W. L., Jr. (2014), 4-D cloud properties from passive satellite data and applications to resolve the flight icing threat to aircraft, *Ph.D. Dissertation*, Univ. Wisconsin-Madison, Madison, WI, 165 pp. [http://www-pm.larc.nasa.gov/icing/pub/WLSDissertation.pdf]